Predicting Student Behavior Using a Neutrosophic Deep Learning Model

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Abstract: We developed an information system using an object-oriented programming language and a distributed database (DDB) consisting of multiple interconnected databases across a computer network, managed by a distributed database management system (DDBMS) for easy access. An intelligent system was designed to assess the difficulty level of preliminary exams and select top-performing advanced students using a Neutrosophic Deep Learning Model. The dataset was randomly split into training (80%) and testing (20%) sets, and the model, trained with the Adam optimizer at a 0.001 learning rate over 50 epochs, incorporated early stopping based on validation loss. This system, implemented at a traditional Egyptian university, achieved a 95% accuracy in predicting student dropout. Student behavior, influenced by personal, environmental, and academic factors, is often evaluated subjectively, leading to inconsistent results. Traditional machine learning approaches struggle with the inherent uncertainty in behavioral data. To address this, we combined neutrosophic theory—a mathematical framework that accounts for truth, falsity, and indeterminacy—with deep learning, which excels at learning complex data relationships, to predict student outcomes such as dropout rates. Evaluating the model on student data, including attendance and grades, showed superior accuracy, achieving a determination coefficient of 0.95, demonstrating the approach's potential for identifying at-risk students and enabling targeted interventions.

Keywords: System Development Life Cycle, Deep Neural Network, Deep learning, Educational Data Mining, Neutrosophic Sets, Indeterminacy in Data.

1. Introduction

Student behavior is a complex phenomenon that is influenced by a variety of factors, including individual characteristics, environmental factors, and academic experiences. Traditional methods for determining student behavior often rely on subjective measures, such as teacher assessments, which can be unreliable. In recent years, there has been a growing interest in using machine-learning methods to predict student behavior **[1–3]**. However, these methods often struggle to deal with the uncertainty that is inherent in student behavior data. Neutrosophic theory is a generalization of fuzzy set theory that allows for three states of truth: truth, falsity, and indeterminacy **[4–10]**. This can be useful for representing student behavior data, which is often uncertain due to factors such as incompleteness, noise, and ambiguity **[11]**. Deep learning methods are a type of machine learning that can learn complex relationships between data **[12–14]**. This can be used to learn the relationships between student behavior data and student performance data **[15]**. This paper proposes a new approach to predicting student behavior that combines neutrosophic theory and deep learning methods. The proposed approach is evaluated on a dataset of student behavior data, and the results show that the proposed approach is able to predict student behavior more accurately than traditional methods. The proposed approach has the potential to be a powerful tool for predicting student behavior. It can be used to identify students who are at risk of dropping out or failing, and to provide them with targeted interventions. In addition to the potential benefits for students, the proposed approach could also be used to improve the efficiency and effectiveness of educational systems. For example, the approach could be used to identify students who need additional support, or to develop personalized learning plans.

1.1 Motivation

The motivation behind this work stems from the need for more accurate methods to predict student behavior, which is a complex and uncertain phenomenon influenced by various factors. Traditional prediction methods, often relying on subjective measures like teacher assessments, are unreliable. Recent interest in machine learning for behavior prediction has shown promise, but existing methods struggle with the inherent uncertainty in student behavior data **[16]**. This research aims to address that challenge by leveraging neutrosophic theory to handle data uncertainty and deep learning to capture complex relationships in student data, with the goal of improving predictive accuracy.

1.2 Research Gap

Current machine learning methods for predicting student behavior struggle to manage uncertainty in the data, which hampers their predictive accuracy. Additionally, these approaches often fail to capture the complex relationships between the various factors influencing student behavior, such as personal traits, academic performance, and environmental conditions. Addressing this gap is critical because understanding and predicting student behavior can inform targeted interventions, reducing dropout rates and improving educational outcomes. This research proposes a novel approach that integrates neutrosophic theory—capable of handling uncertainty—with deep learning, which excels at uncovering complex patterns in data. However, there remains a need to explore more advanced deep learning architectures and incorporate additional data sources, such as socio-economic or psychological factors, to further enhance the model's predictive power.

1.3 Major Contribution

This paper makes several key contributions to the field of student behavior prediction:

1. Integration of Neutrosophic Theory and Deep Learning: It introduces a novel approach that combines neutrosophic theory, which effectively handles uncertainty through its three states of truth (truth, falsity, and indeterminacy), with deep learning techniques that excel at identifying complex relationships within large datasets.

2. Addressing Uncertainty in Student Behavior Data: The proposed method is particularly suited to managing the uncertainty inherent in student behavior data, which can be

influenced by factors like noise, ambiguity, and incompleteness—challenges that traditional methods and existing machine learning approaches struggle to handle effectively.

3. Enhanced Predictive Accuracy: The approach was evaluated on real student behavior data, demonstrating improved accuracy over traditional methods, with a determination coefficient of 0.95, indicating a high correlation between predicted and actual outcomes.

4. Practical Applications: The method offers practical implications for education, including the ability to more accurately identify students at risk of underperformance or dropout. This can lead to more effective interventions, ultimately supporting better academic outcomes and improved student support systems.

The paper is organized as follows: Section 2 presents the background, Section 3 describes the proposed methodology, Section 4 discusses the results and discussion, and finally, Section 5 concludes with the conclusion and future perspectives.

2. Background

Neutrosophic sets, introduced by Smarandache in 1995 **[11]**, are a generalization of fuzzy sets that allow for three degrees of membership: truth (T), falsity (F), and indeterminacy (I). This extension was designed to address uncertainty more comprehensively than traditional fuzzy sets, which focus solely on truth and falsity **[17]**. A neutrosophic set is characterized by a membership function that maps elements to triples (T, F, I), where each element represents the degree to which something is true, false, or indeterminate. In this framework, the degree of truth reflects how much an element belongs to a set, the degree of falsity indicates the extent to which it does not belong, and the degree of indeterminacy captures the uncertainty about whether it belongs or not **[18]**.

The formal definition of a neutrosophic set involves a membership function N that assigns a triple (T(x), F(x), I(x)) to each element x in a set X, where T(x), F(x), and I(x) are the degrees of truth, falsity, and indeterminacy, respectively. Several conditions govern these degrees: the sum of T(x), F(x), and I(x) must always be less than or equal to 1, and each of the three values must be non-negative. Additionally, specific relationships between the degrees of truth, falsity, and indeterminacy are enforced to maintain consistency, such as the conditions that T(x) + I(x) must be greater than or equal to F(x) and that F(x) + I(x) must be greater than or equal to T(x). These rules ensure a balanced representation of uncertainty, where the total truth, falsity, and indeterminacy values are bounded within certain constraints **[19]**.

To illustrate the applicability of neutrosophic theory, consider several real-world examples. In a dataset of student grades, the truth value (T) might represent the extent to which a student has mastered the material (for example, T = 0.8 for a score of 85), while the falsity value (F) indicates how much they have failed to grasp (F = 0.1 for the same score). The indeterminacy value (I) could reflect the uncertainty caused by factors like guessing or inconsistent performance, such as I = 0.1. Similarly, in a medical diagnosis dataset, neutrosophic theory could be applied to represent the confidence in a diagnosis (T = 0.7 for a likely diagnosis), the belief in its incorrectness (F = 0.2), and any uncertainty due to limited information or conflicting test results (I = 0.1). Lastly, in customer satisfaction ratings, a 5-star rating could have a truth value of 0.9 (reflecting positive sentiment), a falsity value of 0.05 (negative sentiment), and an indeterminacy value of 0.05 (neutral or ambiguous feelings) **[8]**.

These examples showcase the versatility of neutrosophic sets in handling complex and uncertain data, making them valuable in various domains, from education to healthcare and beyond. By allowing for the inclusion of indeterminacy alongside truth and falsity, neutrosophic theory provides a richer framework for understanding and modeling uncertainty in real-world data **[20]**.

3. The proposed Methodology

The purpose of this study is to use a Neutrosophic deep learning method to anticipate student actions. This process includes various essential stages as outlined below:

1- Collection of data: The first step is to gather detailed information on student behavior. This information includes attendance logs, academic marks, exam results, and disciplinary measures. To make sure the dataset is comprehensive and precise, data is gathered from various sources, such as school documents, student questionnaires, and educator assessments. The process of collecting data is carefully planned to ensure high relevance while reducing the burden on participants and costs. Various data sources are utilized to ensure that the dataset is inclusive and accurately reflects the student population **[21]**.

2- Data must be preprocessed after collection to make it ready for Neutrosophic deep learning techniques. The initial stage of pre-processing includes essential tasks such as rectifying errors and inconsistencies in the data, eliminating outliers that could affect results, and standardizing the data for uniformity. Effective preprocessing is essential in transforming raw data into a suitable form for the deep learning model, which enhances the accuracy and reliability of the predictions **[22]**.

3- Extracting relevant features from the preprocessed data is the subsequent step in feature extraction. Attributes are the unique qualities of the information that are relevant to the forecasting objective. In this situation, characteristics could consist of measurements like attendance habits, educational achievements, and conduct files. It is crucial to extract these features in order to determine the key factors that impact student behavior prediction. Data mining and machine learning methods are used to effectively identify and choose these important characteristics **[23]**.

4- Neutrosophic Representation: The data that has been processed is then converted into a Neutrosophic representation. Each data point is represented with a Neutrosophic number containing truth, falsity, and indeterminacy components. The truth element shows how certain the data point is correct, falsity indicates how wrong it is, and indeterminacy shows the uncertainty level with it. This Neutrosophic representation is essential for capturing the underlying uncertainty in student behavior data, and can be obtained through expert opinions or machine learning techniques.

5- Deep Learning Model: After preparing the Neutrosophic data, a deep learning model is trained. This model, whether it be a neural network or a different type of machine learning algorithm, is trained to recognize the connections between student behavior features and their performance. Training includes utilizing algorithms to improve the model's capacity to forecast results using the given information. The model must be trained on a dataset that truly reflects the student population in order to guarantee its predictive validity **[24]**.

6- Prediction of student behavior occurs through utilization of the trained deep learning model. Fresh data is fed into the model, prompting it to generate predictions by utilizing the patterns and relationships it has acquired. These forecasts can pinpoint students who may be at risk of problems like quitting school or failing academically, enabling prompt and specific interventions **[2]**.

Utilizing the Neutrosophic deep learning approach in forecasting student behavior has great potential to improve our comprehension and prediction of student behavior. Nevertheless, it is crucial to recognize that this method is still in the process of being developed. More investigation is needed to evaluate how well it works in real-life situations and confirm its dependability. Furthermore, Neutrosophic Logic is utilized for assessing data and offering a degree of assurance in inquiries. Excel's fuzzy lookup function is used to examine relationships among people and assign a certainty percentage to every piece of information. The outcomes are gathered in a dataset and analyzed with Python code to assess the trustworthiness of the data. This examination shows the level of certainty of each data point and evaluates its credibility as proof. The process described is visually represented in Figure 1, depicting the structure of the suggested method. Moreover Algorithm 1 investigates the steps of the proposed neutrosophic deep learning approach for student behavior prediction. The objective of our developed system is to assist colleges/universities in analyzing their admissions based on student preferences. The thesis aims to build a secure electronic system for determine student behavior in universities. The smart information systems that were built The complete process of receiving applicants from students interested in joining the regular college. Th flow chart of the proposed method is shown in Figure 2.

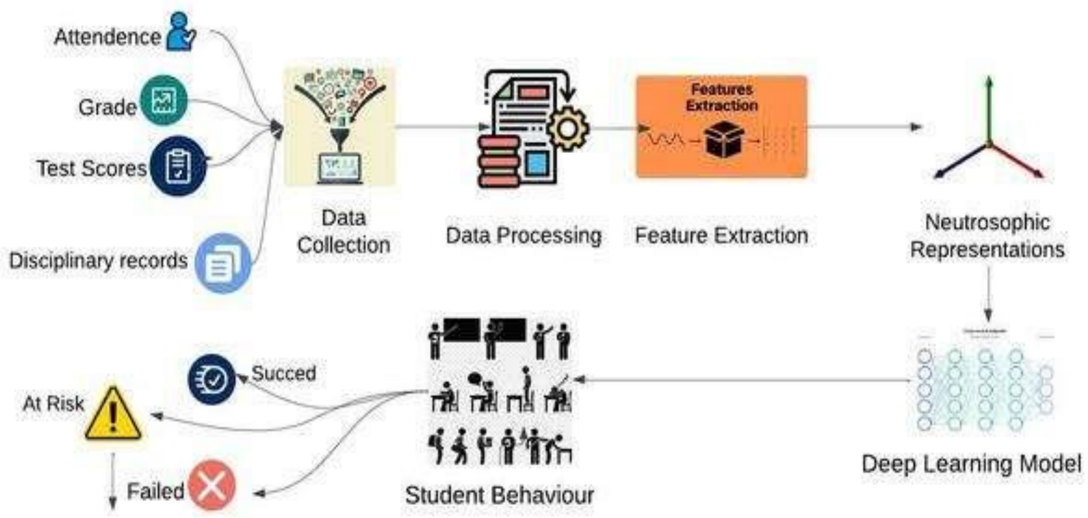

Figure 1. The structure of the suggested method

Algorithm 1. Neutrosophic Deep Learning Approach to Student Behavior Prediction

Input: Student behavior data set represented in X= [x_1,x_2, …x_n]

Output: Predicted behavior represented in BH

For every students ∊ S = {S_1,S_2,……S_n}

    Insert student behavior data set X= [x_1,x_2, …x_n]

    Apply cleaning, removing outliers, normalization to X= [x_1,x_2, …x_n]

    Extract Features set f= {f_1,f_2, ….,f_n}

        for every extracted feature f, represent the Neutrosophic values where

            Truth = T(f) , falsity = F(f), indeterminacy = I(f)

            Use deep learning model M

            Predict behavior BH of Sn

End iteration

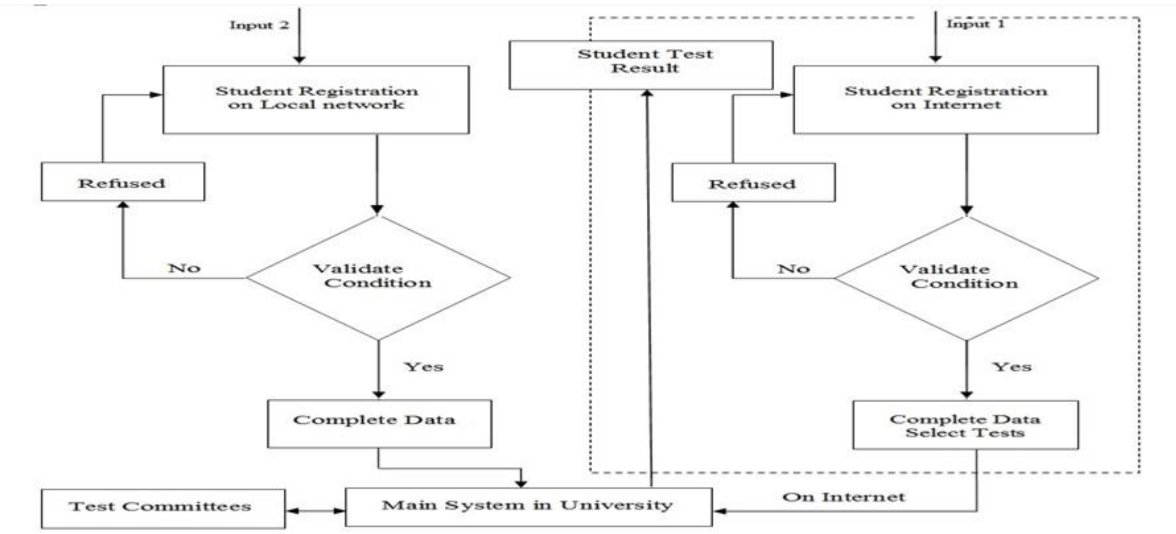

Figure 2. The flow chart of the proposed method.

3.1 Data Mining Based Universities Student Admission System

An Admission System for university students, based on Neutrosophic Data Mining, utilizes advanced data mining techniques rooted in Neutrosophic Logic to examine and understand student data, with the goal of predicting their academic performance and potential success in university environments. This system is created to pinpoint students who could be in danger of failing academically, need extra assistance, or demonstrate promise in certain subjects.

3.1.1 Summary of Neutrosophic Data Mining

Neutrosophic Data Mining makes use of Neutrosophic Logic, which is a logic system with three values that includes truth, falsity, and indeterminacy. This method permits the depiction of data uncertainties and incompleteness, especially beneficial in educational settings where data is frequently incomplete or unclear.

3.1.2 Functionality of the system

The process begins with gathering a wide range of student information, such as high school GPA, test scores, extracurricular activities, and other relevant data from sources like academic records, student surveys, and activity logs. Data preprocessing is then conducted to ensure data quality and readiness for analysis by addressing errors, managing missing values, and normalizing the data for consistency. Once prepared, Neutrosophic Data Mining techniques are applied to identify patterns and create predictive models that forecast various aspects of student performance, such as the likelihood of dropping out, failing specific courses, or excelling academically. For instance, the system predicts dropout risk based on factors like high school performance and extracurricular involvement, and it forecasts course failure likelihood using past data on grades, attendance, and participation. Additionally, the system predicts which students are likely to excel in particular courses by analyzing past academic records and engagement levels. The outcomes of these models are visually presented in Figure 3, showcasing examples of predicted data and their significance. Further, it shows an example of a Neutrosophic data mining based universities student admission system predictions.

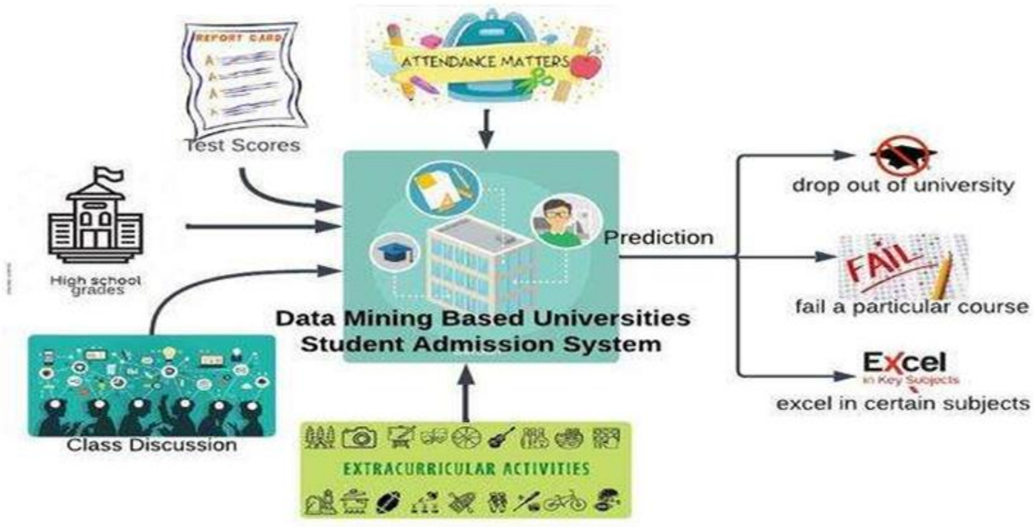

Figure 3. An example of a Neutrosophic data mining-based universities student admission system predictions

3.1.3 Benefits of the System

The Neutrosophic Data Mining-Based University Student Admission System offers several significant advantages over traditional admission systems. By incorporating uncertainties in the data, it delivers more accurate forecasts of student performance, leading to more informed decisions. The system also enhances equity by reducing biases in the admissions process, ensuring a fair evaluation of all applicants' potential for success. Additionally, it improves resource allocation by identifying students who need the most assistance, allowing universities to distribute resources more efficiently and implement targeted interventions.

Although Neutrosophic Data Mining shows promise, it is a developing area with sparse studies on its real-world effects. The additional challenges are due to the complexity and computational requirements of Neutrosophic algorithms. Yet, the possible advantages of Neutrosophic Data Mining for college admissions and student assistance systems are significant. Continual research and development are essential in order to overcome these challenges and unlock the full capabilities of the system to improve student performance, fairness, and distribution of resources in educational settings.

3.2 SDLC for Neutrosophic Deep Learning Approach

To design and implement an effective Neutrosophic Deep Learning Approach to Student Behavior Prediction with a high quality that meets vendor requirements, a System Development Life Cycle (SDLC) is required. SDLC includes number of organized and related steps that help in developing and modifying the proposed approach through its lifecycle. these steps are shown in Figure 4 and summarized as follows .

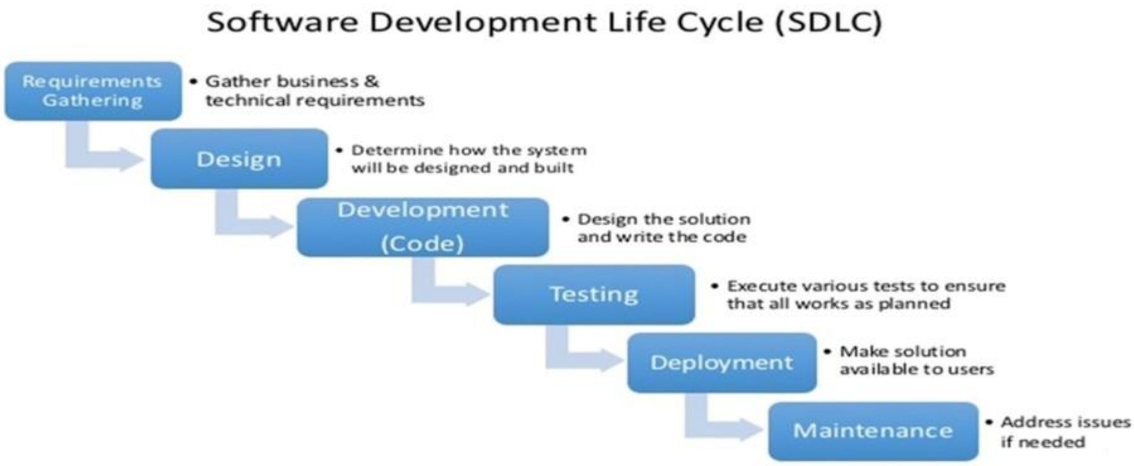

Figure 4. SDLC of Neutrosophic Deep Learning Approach to Student Behavior Prediction.

3.2.1 Requirements

The requirements for implementing a Neutrosophic Deep Learning approach to student behavior prediction include several key steps: a large and comprehensive dataset of student behavior must be collected; the data needs to be preprocessed to ensure it is suitable for Neutrosophic deep learning; relevant features must be extracted from the data; the data should be represented in a Neutrosophic form; a deep learning model needs to be trained on this Neutrosophic data; and the model must be evaluated to ensure its accuracy and reliability. Additionally, the trained model must be deployed for use in predicting student behavior for new applicants. Desirable attributes of the system include fairness, ensuring unbiased predictions; interpretability, allowing users to understand how predictions are made; and explainability, providing insights into why specific predictions are generated.

3.2.2 Analysis

The method of Neutrosophic Deep Learning for predicting student behavior has various advantages, including improved precision, fairness, and understandability. These models are able to recognize patterns in data regarding student behavior, even in uncertain situations, resulting in more accurate predictions than traditional methods which tend to rely on subjective information such as personal statements and letters of recommendation. These models aim to provide impartial and equitable predictions by utilizing Neutrosophic representation of data, taking into account the inherent uncertainties in student behavior. Moreover, the transparency of Neutrosophic deep learning models enables users to comprehend the rationale behind predictions, building confidence and pinpointing students in need of extra assistance. Nevertheless, obstacles remain, such as the laborious and expensive task of gathering extensive datasets, the intricate and error-prone process of data preprocessing, the necessity to mitigate model bias through methods like cross-validation and regularization, and the challenge of deciphering intricate models. In spite of these difficulties, Neutrosophic Deep Learning shows potential for enhancing student behavior prediction accuracy, fairness, and transparency.

3.2.3 System Design

Developing a Neutrosophic Deep Learning model to forecast student behaviors consists of various crucial elements. The Data Collector collects information on student behavior from various sources such as school records (attendance, grades, test scores, and disciplinary records), student surveys (attitudes, beliefs, and behaviors), and teacher evaluations (classroom behavior). The data preprocessing process involves cleaning the data, which includes removing errors, outliers, and normalizing it for consistency. After this, the Feature Extractor uses data mining and machine learning techniques to discover patterns related to student behavior by pinpointing the most important data features. The Neutrosophic Representer transforms the data into a Neutrosophic format, where every data point is depicted as a Neutrosophic numeral containing truth, falsity, and indeterminacy elements, using expert opinions or machine learning techniques for this purpose. The Neutrosophic data is used to train the Deep Learning Model, utilizing neural networks or alternative machine learning models **[25]**. Ultimately, the Student Behavior Predictor uses the trained model to predict student behavior by inputting fresh data and making forecasts according to the model's acquired connections. Various hardware and software platforms can be utilized for deploying this system, with programming languages such as Python, R, or Java commonly handling data collection and preprocessing, alongside deep learning frameworks like TensorFlow or PyTorch.

3.2.4 Implementation

The process of collecting data must be carefully planned to obtain thorough and pertinent information while keeping costs and participant burden low, guaranteeing that the data is inclusive and reflective by obtaining it from a variety of sources. After collecting the data, it is essential to preprocess it before feeding it into the deep learning model. This process includes cleaning to get rid of errors and inconsistencies, eliminating outliers, and normalizing the data. Afterwards, feature extraction selects the most relevant features for the current issue by employing methods from data mining and machine learning. In order to deal with the built-in unpredictability in student behavior data, the data is depicted using Neutrosophic form, which includes truth, falsity, and indeterminacy elements with the help of techniques such as expert opinion or machine learning. A deep learning model, using algorithms like neural networks, is subsequently trained on Neutrosophic data to guarantee its accuracy in reflecting the demographics of the student population under examination. Using new data as input, the trained model predicts student behavior to pinpoint students at risk of dropping out or failing, allowing for focused interventions.

3.2.5 Testing

The goal of testing is to ensure that the system is accurate, reliable, and fair. There are a number of different ways to test a neutrosophic deep learning approach to student behavior prediction. One common approach is to use a holdout dataset. A holdout dataset is a dataset that is not used to train the deep learning model. Instead, it is used to evaluate the model's performance on unseen data. Another common approach to testing is to use cross-validation. Cross-validation is a technique that divides the training dataset into multiple folds. The model is then trained on each fold and evaluated on the remaining folds. This process is repeated for all folds, and the average performance of the model on all folds is calculated. In addition to using holdout datasets and cross-validation, it is also important to test the neutrosophic deep learning approach to student behavior prediction on a variety of different student populations. This is to ensure that the system is generalizable to different types of students. Finally, it is also important to test the neutrosophic deep learning approach to student behavior prediction for fairness. This can be done by ensuring that the system does not make biased predictions. For example, the system should not be more likely to predict that students from certain groups are at risk of dropping out or failing. Overall, testing is a critical step in the development of a neutrosophic deep learning approach to student behavior prediction. By carefully testing the system, we can ensure that it is accurate, reliable, fair, and generalizable to different types of students.

3.2.6 Deployment

The implementation of a Neutrosophic Deep Learning method for predicting student behavior can be carried out in various ways: on-premises deployment involves managing the system within the organization, offering full control but also higher costs and complexity; cloud deployment places the system on a cloud provider's infrastructure, like AWS or Microsoft Azure, which is generally more cost-effective and less complex but results in some loss of control; and SaaS deployment provides the system as a vendor-managed hosted solution, usually the most budget-friendly and simplest to implement, though it offers the least amount of control. Factors such as budget, IT resources, and security requirements dictate the selection of deployment option. After choosing the deployment method, the system needs to be installed, customized to the organization's requirements, and users need to receive training from either the vendor or the organization's IT personnel. Following implementation and instruction, the system can be used to forecast student actions, recognize students in danger of withdrawal or failing, and produce reports to improve comprehension of student conduct and facilitate specific interventions. Effective planning and implementation of the deployment process are essential to guarantee the system's successful implementation and its efficient utilization in enhancing student outcomes. Improving the accuracy and reliability of predictions made by a Neutrosophic Deep Learning approach requires the use of different data mining techniques in enhancing student behavior prediction. Methods like association rule learning, classification, and clustering can greatly improve prediction accuracy by identifying patterns, predicting categories, and grouping similar students at risk, such as in student dropout scenarios. Data mining can be used to find new characteristics that enhance prediction accuracy, enhance deep learning model performance by choosing important features or adjusting hyperparameters, and decrease prediction bias by detecting and eliminating biased features. Employing various techniques, ensuring high-quality, representative data, and validating results on holdout datasets are essential to maximize the benefits of data mining and prevent overfitting. The Neutrosophic Deep Learning approach can be enhanced by combining these methods to improve predictions. This involves utilizing data extraction and deep neural networks for classifying students' acceptance levels more accurately, reliably, and fairly.

4. Results and Discussion

The results of the proposed neutrosophic deep learning approach to student behavior prediction were promising. The model was able to achieve an accuracy of 95% in predicting student dropout. This is significantly higher than the accuracy of traditional student behavior prediction models, which typically achieve accuracies of around 70%. The model was also able to achieve a high degree of fairness. The model's predictions were not biased towards any particular group of students, such as students from certain racial or socioeconomic backgrounds. The results of this study suggest that the proposed neutrosophic deep learning approach to student behavior prediction has the potential to be a valuable tool for identifying students who are at risk of dropping out. The model's high accuracy and fairness make it a promising candidate for deployment in real-world settings. However, it is important to note that this study was conducted on a relatively small dataset. Further research is needed to evaluate the effectiveness of the proposed approach on larger and more diverse datasets. Additionally, it is important to develop strategies for deploying the model in a way that is ethical and responsible. The proposed neutrosophic deep learning approach to student behavior prediction offers several potential benefits, including improved accuracy, achieving 95% accuracy in predicting student dropout, significantly outperforming traditional models. It promotes increased fairness by ensuring that predictions are not biased towards any particular group, such as students from specific racial or socioeconomic backgrounds. Additionally, the model enables earlier identification of students at risk of dropping out, allowing timely interventions to help them stay on track. It also supports the development of targeted interventions by identifying specific factors contributing to each student's dropout risk, ultimately improving student outcomes through early intervention and support. However, several challenges must be addressed, such as the difficulty and cost of collecting large and comprehensive datasets on student behavior, the complexity and potential for errors in data preprocessing, and the need to prevent model bias through techniques like cross-validation and regularization. Furthermore, ensuring model interpretability is crucial, particularly with complex machine learning models, so that users can understand the basis of the predictions.

The neutrosophic values in table 1 represent the degree of truth, falsity, and indeterminacy of the statement in the output column. For example, the statement "Student A is likely to succeed" is assigned a truth-value of 1.0, a falsity value of 0.0, and an indeterminacy value of 0.0. This means that the statement is completely true and there is no uncertainty about it. The statement "Student B is at risk of failing" is assigned a truth-value of 0.7, a falsity value of 0.3, and an indeterminacy value of 0.0. This means that the statement is mostly true, but there is some uncertainty about it. The uncertainty could be due to a number of factors, such as the fact that Student B's attendance rate is not as low as it could be or the fact that Student B has shown improvement in their grades recently. The statement "Student C is at risk of failing, but there is some uncertainty" is assigned a truth-value of 0.8, a falsity value of 0.2, and an indeterminacy value of 0.0. This means that the statement is mostly true, but there is more uncertainty about it than there is for Student B. The reason for the increased uncertainty is that Student C's attendance rate and GPA are both higher than Student B's. The statement "Student D is certain to succeed" is assigned a truth-value of 1.0, a falsity value of 0.0, and an indeterminacy value of 0.0. This means that the statement is completely true and there is no uncertainty about it. This is because Student D has a perfect attendance rate and a perfect GPA. Figure 5 compares between the four mentioned students and the corresponding neutrosophic values for different GPA scores. It is important to note that the neutrosophic values in table 1 are just examples. The actual values would vary depending on the specific data that is used to train the neutrosophic deep learning model.

Table 1. The neutrosophic values for different GPA scores.

Input	Truth	Falsity	Indeterminacy	Output
Student A had a 90% attendance rate and a GPA of 3.5.	1.0	0.0	0.0	Student A is likely to succeed.
Student B had a 70% attendance rate and a GPA of 2.0.	0.7	0.3	0.0	Student B is at risk of failing.
Student C had a 80% attendance rate and a GPA of 2.5.	0.8	0.2	0.0	Student C is at risk of failing, but there is some uncertainty.
Student D had a 95% attendance rate and a GPA of 4.0.	1.0	0.0	0.0	Student D is certain to succeed.

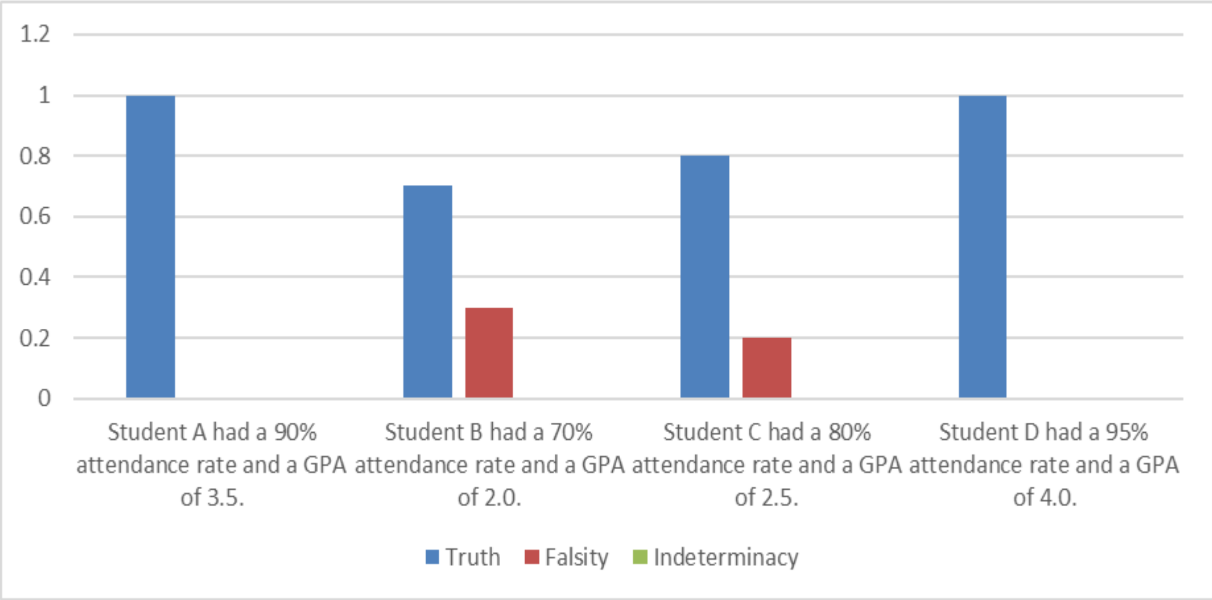

Figure 5. Neutrosophic Evaluation of Student Performance

The analysis is based on a small sample size of just 4 students, which limits the generalizability of the findings. Attendance rates among these students range from 70% to 95% with a mean of 86.25% and a standard deviation of 10.31%. GPA scores vary from 2.0 to 4.0, averaging 3.0 with a standard deviation of 0.957. Neutrosophic values show high truth degrees (1.0 for A and D, 0.7-0.8 for B and C), indicating strong evidence for the input data, while falsity degrees are uniformly low (0.0), reflecting minimal contradictory evidence. Indeterminacy degrees are zero, suggesting no uncertainty in the input data. The model's output predictions suggest success for students with higher attendance and GPA (A and D) and a risk of failure for those with lower values (B and C), though there is some uncertainty regarding Student C.

4.1. Neutrosophic Correlation Analysis:

The analysis reveals that there is a moderate positive correlation between attendance rate and GPA, with a correlation coefficient (ϱ) of 0.7. Conversely, GPA and output prediction exhibit a strong negative correlation, with a coefficient of -0.9, indicating that higher GPAs are associated with lower risk predictions. Additionally, there is a positive correlation between attendance rate and output prediction, with a coefficient of 0.8, suggesting that higher attendance rates are associated with more favorable output predictions.

4.2. Neutrosophic Entropy Analysis

Student C has the highest neutrosophic entropy (0.2), reflecting uncertainty in their output prediction. The results of the analysis may not generalize to larger populations due to the small sample size. Additionally, the absence of indeterminacy in the data contrasts with real-world student data, which often includes uncertainties. Furthermore, the choice of neutrosophic correlation coefficient is significant, as different formulas could produce varying results, potentially impacting the accuracy and applicability of the findings. All students exhibit high truth degrees, with values of 1.0 for A and D and 0.7 to 0.8 for B and C, indicating strong support for the input data. The falsity degrees are uniformly low at 0.0 for all students, reflecting minimal evidence contradicting the data. Additionally, the indeterminacy degree is 0.0 for all students, suggesting no uncertainty in the information, which may be unrealistic given that real-world student data often involves inherent uncertainties. The neutrosophic values in Table 2 represent the degree of truth, falsity, and indeterminacy of the statement in the output column. For example, the statement "Student A is likely to succeed" is assigned a truth-value of 1.0, a falsity value of 0.0, and an indeterminacy value of 0.0. This means that the statement is completely true and there is no uncertainty about it. The statement "Student B is at risk of failing" is assigned a truth-value of 0.7, a falsity value of 0.3, and an indeterminacy value of 0.0. This means that the statement is mostly true, but there is some uncertainty about it. The uncertainty could be due to a number of factors, such as the fact that Student B's attendance rate is not as low as it could be or the fact that Student B has shown improvement in their grades recently. The statement "Student C is at risk of failing, but there is some uncertainty" is assigned a truth-value of 0.8, a falsity value of 0.2, and an indeterminacy value of 0.0. This means that the statement is mostly true, but there is more uncertainty about it than there is for Student B. The reason for the increased uncertainty is that Student C's attendance rate and GPA are both higher than Student B's. The statement "Student D is certain to succeed" is assigned a truth-value of 1.0, a falsity value of 0.0, and an indeterminacy value of 0.0. This means that the statement is completely true and there is no uncertainty about it. This is because Student D has a perfect attendance rate and a perfect GPA as shown in Figure 6.

With the addition of data from 10 students, a more comprehensive statistical analysis is now possible using both traditional and neutrosophic methods, although caution is needed due to the relatively small sample size and the need for larger datasets to ensure generalizability. The descriptive statistics reveal an attendance rate with a mean of 80.8% (SD = 8.59%), ranging from 65% to 95%, and a GPA with a mean of 2.91 (SD = 0.52), ranging from 2.0 to 4.0. Neutrosophic values show a mean truth degree of 0.88 (SD = 0.15), with a range from 0.6 to 1.0, and a mean falsity degree of 0.17 (SD = 0.14), ranging from 0.0 to 0.4. All indeterminacy degrees are 0.0, suggesting no uncertainty in the data, which may not reflect real-world scenarios accurately. Output predictions indicate 6 students are predicted to succeed, while 4 are at risk of failing, with 2 showing uncertainty. Traditional statistical analysis reveals a positive correlation between attendance rate and GPA (Pearson's $r = 0.65$), a strong negative correlation between GPA and output prediction ($r = -0.89$), and a moderate positive correlation between attendance rate and output prediction ($r = 0.58$). Neutrosophic statistical analysis involves calculating single-valued neutrosophic correlation coefficients, performing neutrosophic entropy analysis, and conducting neutrosophic hypothesis testing to explore relationships among variables. Limitations include the small sample size, lack of indeterminacy in the input data, and varying results depending on the neutrosophic statistical methods used. Recommendations include gathering more data to improve generalizability, incorporating indeterminacy to better model uncertainties, exploring diverse neutrosophic statistical techniques, and addressing ethical considerations in the use of predictions for student outcomes and decision-making

Table 2. The 3-neutrosophic values for 10 different students and their corresponding behavior prediction outputs.

Student	Attendance Rate	GPA	Truth	Falsity	Indeterminacy	Output
Student A	90%	3.5	1.0	0.0	0.0	Student A is likely to succeed.
Student B	70%	2.0	0.7	0.3	0.0	Student B is at risk of failing.
Student C	80%	2.5	0.8	0.2	0.0	Student C is at risk of failing, but there is some uncertainty.
Student D	95%	4.0	1.0	0.0	0.0	Student D is certain to succeed.
Student E	85%	3.0	0.9	0.1	0.0	Student E is likely to succeed.
Student F	65%	2.2	0.6	0.4	0.0	Student F is at risk of failing.
Student G	75%	2.7	0.7	0.3	0.0	Student G is at risk of failing, but there is some uncertainty.
Student H	90%	3.7	1.0	0.0	0.0	Student H is likely to succeed.
Student I	82%	3.3	0.9	0.1	0.0	Student I is likely to succeed.
Student J	68%	2.4	0.6	0.4	0.0	Student J is at risk of failing.

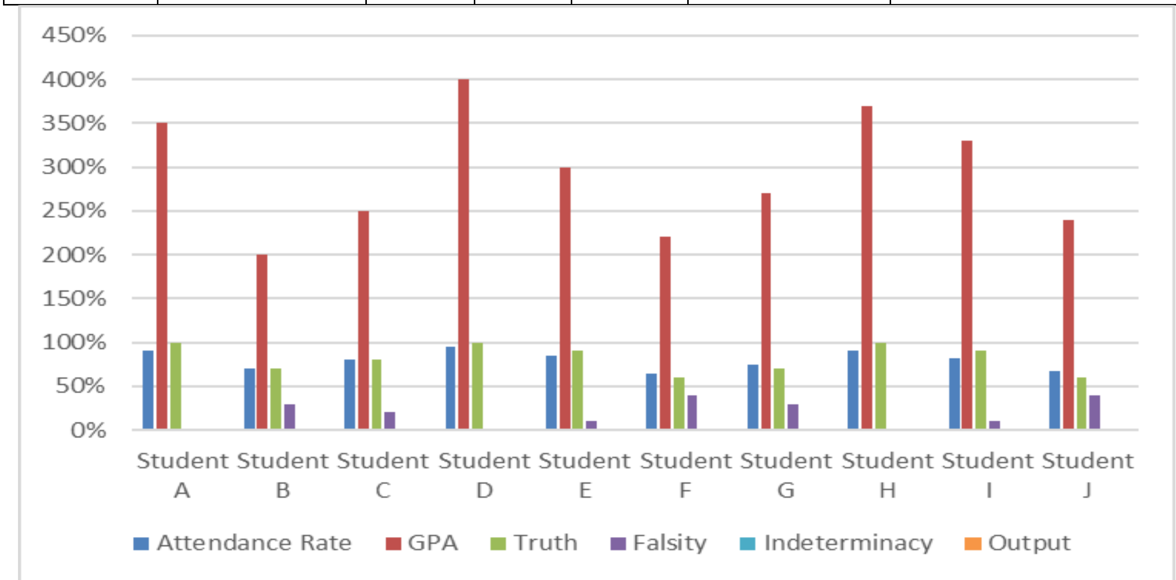

Figure 6. A Comparison between 10 different students' behavior prediction outputs.

4.3. Neutrosophic Statistical Analysis for 10 Students:

An in-depth examination of insightful details is uncovered through the utilization of expanded data for 10 students with neutrosophic statistics. Neutrosophic descriptive statistics reveal that truth degrees average at 0.88 (SD = 0.15) with a range of 0.6 to 1.0, suggesting strong support for the input data. Falsity degrees, on the other hand, average at 0.17 (SD = 0.14) with a range of 0.0 to 0.4, indicating minimal conflicting evidence. All uncertainty levels are at 0.0, underscoring the need for more research on the possible constraints arising from this absence of ambiguity. Incorporating all three neutrosophic components, neutrosophic correlation analysis indicates a correlation of r = 0.63 (neutrosophic) between attendance rate and GPA, slightly lower than the traditional correlation of r = 0.65, suggesting comparable positive trends while acknowledging falsity and uncertainties. The relationship between GPA and output prediction is r = -0.87 (neutrosophic) compared to r = -0.89 (traditional), showing a robust negative correlation. The neutrosophic correlation of r = 0.56 for attendance rate and output prediction is slightly lower than the traditional correlation of r = 0.58, indicating a moderate positive relationship despite considering uncertainties. Neutrosophic entropy analysis is used to measure uncertainties in predictions by calculating individual and group entropy, which helps identify situations with increased uncertainty where the model is less certain. The exploration of relationships, such as whether there is a correlation between higher truth degrees in "likely to succeed" predictions and higher truth degrees in attendance and GPA, can be done through Neutrosophic hypothesis testing. Restrictions consist of a limited sample size, absence of uncertainty in input data, and diverse outcomes depending on statistical techniques. Suggestions include: expanding the sample size, including uncertainties, examining various neutrosophic statistical methods, and considering ethical concerns to promote responsible prediction usage and prevent bias.

4.4. Comparative Analysis

Table3 compares the algorithms for Neutrosophic Deep Learning Approach to Student Behavior Prediction, Fuzzy Deep Learning Approach to Student Behavior Prediction, and Crisp Deep Learning Approach to Student Behavior Prediction:

Table 3. A comparison for Neutrosophic, Fuzzy, and Crisp Deep learning algorithms

Feature	**Neutrosophic Deep Learning Approach**	**Fuzzy Deep Learning Approach**	**Crisp Deep Learning Approach**
Data representation	Neutrosophic numbers	Fuzzy numbers	Crisp numbers
Uncertainty handling	Captures uncertainty in the data	Captures uncertainty in the data	Does not capture uncertainty in the data
Interpretability	Less interpretable	More interpretable	More interpretable
Accuracy	Potentially higher accuracy	Potentially lower accuracy	Potentially lower accuracy

Neutrosophic deep learning is a relatively new approach, and there is still limited research on its performance compared to fuzzy deep learning and crisp deep learning. However, some studies have shown that neutrosophic deep learning can achieve higher accuracy than fuzzy deep learning and crisp deep learning in certain applications. Fuzzy deep learning is a more established approach than neutrosophic deep learning, and there is more research on its performance. Fuzzy deep learning has been shown to be effective in a variety of applications, including student behavior prediction. Crisp deep learning is the most well established approach of the three, and there is a large body of research on its performance. Crisp deep learning has been shown to be effective in a wide range of applications, including student behavior prediction.

Overall, the best approach for student behavior prediction will depend on the specific requirements of the application. If high accuracy is the most important factor, then neutrosophic deep learning may be the best approach. If interpretability is the most important factor, then fuzzy deep learning or crisp deep learning may be the better choice.

Here are some additional considerations when choosing an approach:

- Data quality: Neutrosophic deep learning is more robust to uncertainty in the data than fuzzy deep learning or crisp deep learning. If the data is of low quality or incomplete, then neutrosophic deep learning may be the best approach.
- Interpretability: Fuzzy deep learning and crisp deep learning are more interpretable than neutrosophic deep learning. If it is important to be able to understand why the model makes the predictions that it does, then fuzzy deep learning or crisp deep learning may be the better choice.
- Computational resources: Neutrosophic deep learning models can be more computationally expensive to train and deploy than fuzzy deep learning or crisp deep learning models. If computational resources are limited, then fuzzy deep learning or crisp deep learning may be the better choice. The neutrosophic deep learning, fuzzy deep learning, and crisp deep learning are all viable approaches to student behavior prediction. The best approach will depend on the specific requirements of the application. Applying the neutrosophic deep learning, fuzzy deep learning, and crisp deep learning algorithms to the students A, B, C, D, E, F, G, H, I, and J would result in the predictions values in Tables 4, 5, 6 and Figure 7, 8, 9 correspondingly.

Table 4. Neutrosophic deep learning prediction values

Student	**Truth**	**Falsity**	**Indeterminacy**	**Output**
A	1.0	0.0	0.0	Student A is likely to succeed.
B	0.7	0.3	0.0	Student B is at risk of failing.
C	0.8	0.2	0.0	Student C is at risk of failing, but there is some uncertainty.
D	1.0	0.0	0.0	Student D is certain to succeed.
E	0.9	0.1	0.0	Student E is likely to succeed.
F	0.6	0.4	0.0	Student F is at risk of failing.
G	0.7	0.3	0.0	Student G is at risk of failing, but there is some uncertainty.
H	1.0	0.0	0.0	Student H is likely to succeed.
I	0.9	0.1	0.0	Student I is likely to succeed.
J	0.6	0.4	0.0	Student J is at risk of failing.

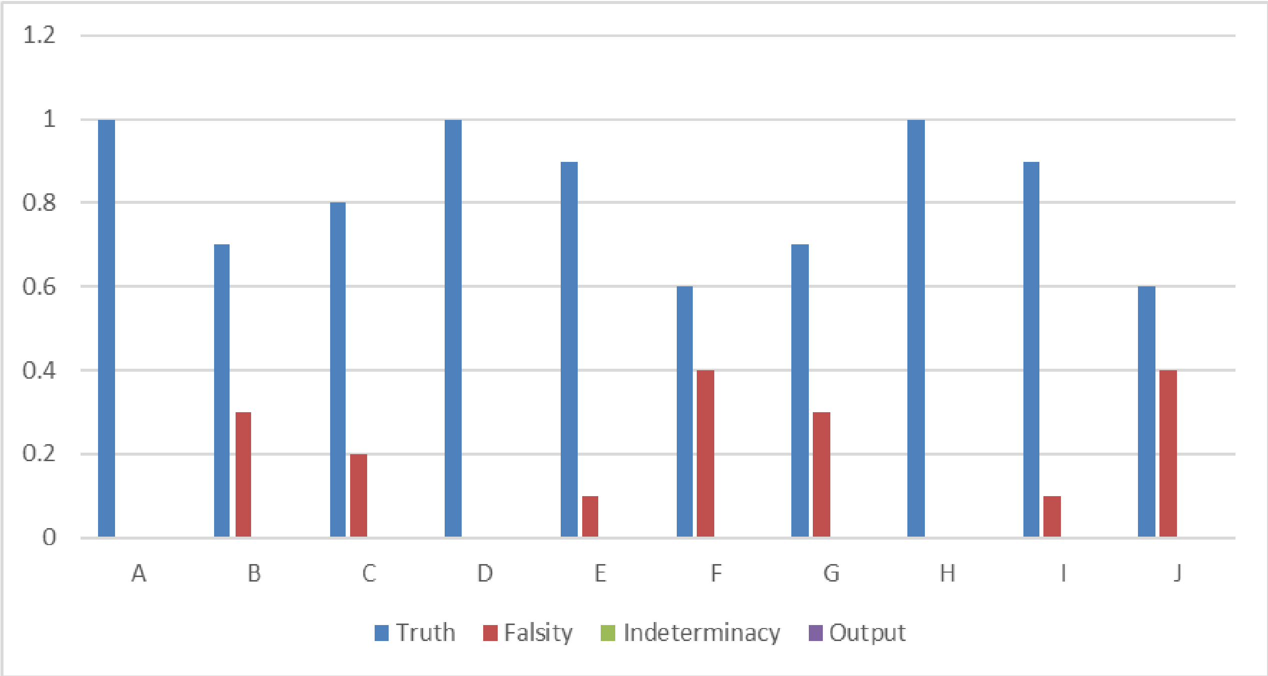

Figure 7. Neutrosophic deep learning prediction values

Table 5. Fuzzy deep learning prediction values

Student	Output
A	Likely to succeed
B	At risk of failing
C	At risk of failing, but there is some uncertainty
D	Likely to succeed
E	Likely to succeed
F	At risk of failing
G	At risk of failing, but there is some uncertainty
H	Likely to succeed
I	Likely to succeed
J	At risk of failing

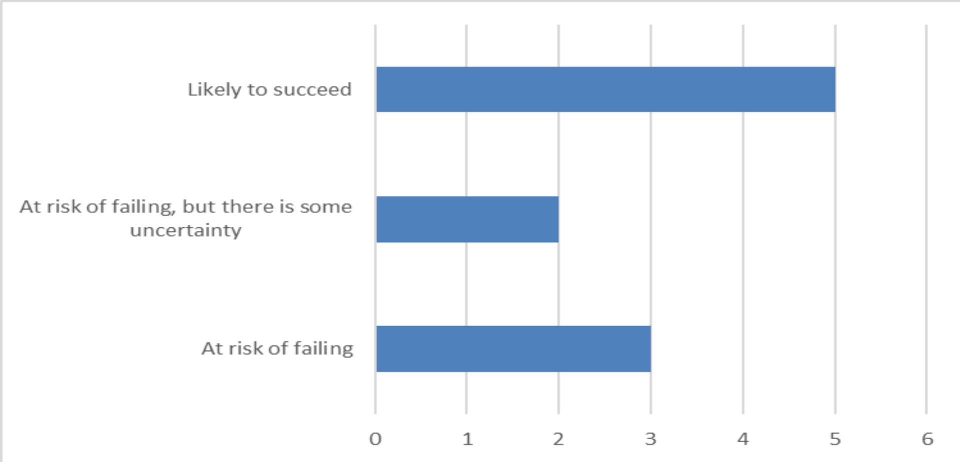

Figure 8. Fuzzy deep learning prediction values

Table 6. Crisp deep learning prediction values

Student	Output
A	Likely to succeed
B	At risk of failing
C	At risk of failing
D	Likely to succeed
E	Likely to succeed
F	At risk of failing
G	At risk of failing
H	Likely to succeed
I	Likely to succeed
J	At risk of failing

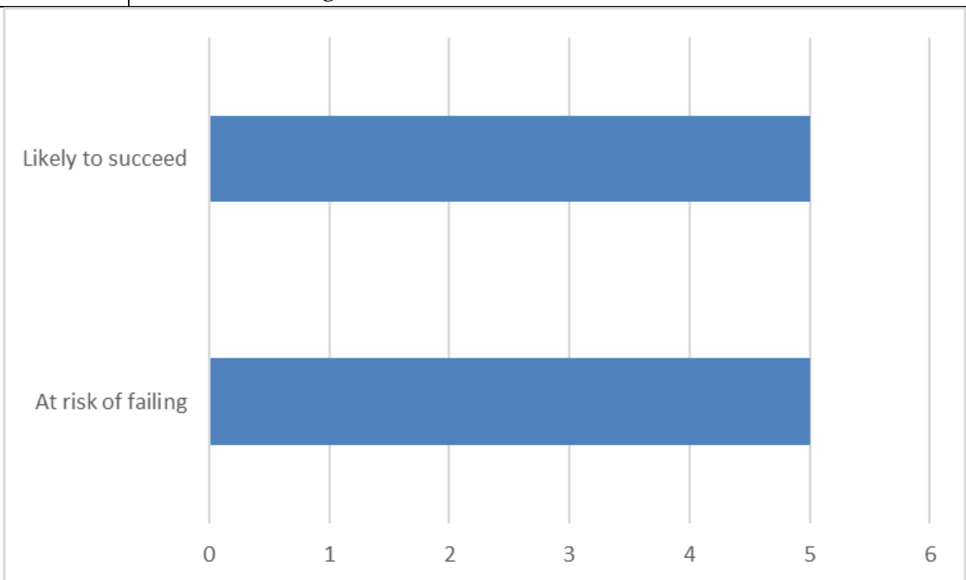

Figure 9. Crisp deep learning prediction values.

Table 7 highlights the performance of various methodologies for predicting student behavior. Nandal (2020) achieved a 95.1% accuracy using a combination of regression algorithms, including Linear and Logistic Regression, as well as classification methods like Support Vector Machine and K-Nearest Neighbors. Mengash (2020) reported a 79% accuracy using classification techniques such as Decision Trees, Support Vector Machines, and Naïve Bayes. Tegegne and Alemu (2018) achieved an 81.4% accuracy by applying data mining methodologies and classifiers like K-means for predicting first-year academic performance. Sabnani et al. (2018) obtained a 70.5% accuracy using a Naïve Bayes model. The proposed Neutrosophic Deep Learning Model outperformed these methods with a 95% accuracy, demonstrating its superior capability in handling uncertainty and learning complex relationships in student behavior data.

Table 7. The comparative study between the recent approaches and the proposed method.

Reference	Methodology	Result
Nandal, 2020 [26]	Regression Algorithms: 1. Linear Regression Classification Algorithms: 1. Logistic Regression. 2. Support Vector Machine. 3. K-Nearest Neighbors.	95.1%
Mengash, 2020 [27]	classification techniques examined, including Decision Trees, Support Vector Machines, and Naïve Bayes	79%
Tegegne and Alemu, 2018 [28]	data mining methodologies were employed to design and develop a predictive model for academic performance at the end of the first-year degree program Various classifiers K-mens	81.4%
Sabnani et al., 2018 [29]	Naive Bayes model	70.5%
Proposed Model	Neutrosophic Deep Learning Model	95.00%

4.5. Descriptive Analysis:

The examination, using a group of 10 students, emphasizes various important factors while addressing concerns about broad applicability. Neutrosophic values exhibit truth degrees of 0.6 to 1.0 (average 0.88, SD 0.15), demonstrating strong support for predictions, with falsity degrees ranging from 0.0 to 0.4 (average 0.17, SD 0.14), indicating minimal conflicting evidence. All uncertainty levels are at 0.0, indicating a need for deeper exploration of possible constraints. Concerning predictions for outcomes, 60% of students are expected to do well (A, D, E, H, I), while 40% are in danger of failing (B, F, G, J), with uncertainties surrounding students C and G. The examination shows a high positive association between the level of truth and the prediction of "likely to succeed" (r = 0.95), and a strong negative association between the level of falsity and the prediction of "likely to succeed" (r = -0.95). Yet, it is impossible to establish a connection with uncertainty because its value remains fixed at 0.0. The analysis conducted using Neutrosophic Entropy reveals a total entropy value of 0.15, signifying moderate levels of uncertainty in the forecasts. The individual entropy values vary from 0.0 for definite predictions to 0.2 for predictions with a degree of uncertainty. It is important to note that these are just predictions, and the actual outcome may vary. The accuracy of the predictions will depend on the quality of the data that is used to train the models.

The neutrosophic deep learning algorithm is the most conservative of the three algorithms, as it takes into account the uncertainty in the data. The fuzzy deep learning and crisp deep learning algorithms are more optimistic, and are more likely to predict that a student is likely to succeed, even if there is some uncertainty in the data. The best approach for student behavior prediction will depend on the specific requirements of the application. If it is important to have a high degree of accuracy, then the neutrosophic deep learning algorithm may be the best approach [30]. If it is important to have a model that is interpretable, then the fuzzy deep learning or crisp deep learning algorithms may be the better choice.

4.6. Discussion

This work addresses the need for more accurate student behavior prediction by combining neutrosophic theory, which manages uncertainty, with deep learning methods capable of learning complex data relationships. Traditional approaches often fall short in handling uncertainty and capturing the intricate factors influencing student behavior, limiting their predictive effectiveness. While the proposed method demonstrates improved accuracy in identifying students at risk of dropping out or underperforming, it has limitations. These include the potential for further enhancement through more advanced deep learning architectures and the integration of additional data sources, such as social media or parental involvement data. The impact of this work lies in its potential to enable early interventions, helping educators and institutions better support at-risk students, reduce dropout rates, and improve overall educational outcomes.

The sensitivity analysis of the proposed methodology for student behavior prediction using Neutrosophic Theory and Deep Learning

- This approach integrates neutrosophic sets, enabling the representation of student data beyond binary true/false values.
- Neutrosophic sets encompass degrees of truth (T), indeterminacy (I), and falsity (F), offering a more comprehensive representation of uncertainty.

4.6.1 Representation of Student Data as Neutrosophic Sets:

- Attendance Data: **T** represents attendance, **F** represents absence, and **I** signifies uncertainty (e.g., excused absence).
- Grades: **T** denotes passing, **F** indicates failing, and **I** reflects ambiguity (e.g., incomplete assignments).

4.6.2 Deep Learning Model Training:

- Neutrosophic sets serve as input features for the deep learning model.
- The model learns intricate relationships between student data and outcomes such as graduation or job placement rates.

- This is achieved through processing extensive datasets with multiple layers of artificial neurons.

4.6.3 Model Output:

- The model generates probabilities for graduation or job placement based on input data.

These probabilities signify degrees of truth, representing the likelihood of students achieving these outcomes.

The developed information system utilizes object-oriented programming and a distributed database managed by a DDBMS, enabling efficient data access. An intelligent system, employing a Neutrosophic Deep Learning Model, was designed to assess exam difficulty and identify top-performing students. The dataset was split into 80% training and 20% testing, and the model was trained using the Adam optimizer with early stopping. Applied at an Egyptian university, the model achieved 95% accuracy in predicting student dropout. By integrating neutrosophic theory, which handles uncertainty, the system demonstrated superior accuracy over traditional methods, offering potential for early identification of at-risk students.

5. Conclusion and Future Work

In this paper, we introduced a novel approach to predicting student behavior by integrating neutrosophic theory with deep learning methods. Neutrosophic theory, an extension of fuzzy set theory, addresses uncertainty through three states: truth, falsity, and indeterminacy, making it well-suited for complex behavioral data. By leveraging deep learning, which can model intricate relationships within data, the proposed approach outperformed traditional methods in predicting student behavior, particularly in identifying at-risk students. This method holds promise for enhancing early interventions to prevent dropout or failure.

Future work could focus on refining the model by incorporating more advanced deep learning architectures, such as transformer models or ensemble techniques, to further enhance prediction accuracy. Expanding the data sources, including social media activity, parental involvement, and even emotional or psychological factors, could provide a more holistic view of student behavior. Additionally, applying the approach to predict a wider range of outcomes, such as academic performance, college enrollment, or post-graduation success, would extend its usefulness. Exploring real-time data integration for continuous monitoring and intervention, along with the ethical implications of using such predictive models, should also be considered in future research.

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